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ADAPTIVE PARALLEL SUBGRADIENT PROJECTION TECHNIQUES WITH INPUT SLIDING TECHNIQUE FOR STEREOPHONIC ACOUSTIC ECHO CANCELLATION

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ABSTRACT

In this paper, we present a novel adaptive filtering scheme for Stereophonic Acoustic Echo Cancellation (SAEC). The proposed scheme is based on the *adaptive parallel subgradient projection techniques* (Yamada *et. al.*, 2002) combined with the *input sliding technique* (Joncour and Sugiyama, 1998, Sugiyama, Joncour, Hirano, 2001). The scheme uses information both in the current and previous periods of the input sliding technique simultaneously while the original technique just uses information in the current period. Robustness to noise is achieved by introducing the stochastic property sets. Moreover it requires only linear computational complexity because it is free from solving systems of linear equations. The numerical example shows that the proposed scheme can achieve, even in noisy situation, much faster convergence as well as lower miss-identification of echo paths and higher ERLE than the conventional technique.

1. INTRODUCTION

Stereophonic acoustic echo cancelers (SAECRs) become one of the keys in successful realizations of high quality hands-free systems, such as advanced teleconferencing, car-phones, home entertainment etc. In a teleconference with several talkers, for example, the auditory images in perceptual space would help us to localize each talker. The principal part of SAECR is illustrated in Fig. 1. Since the 2 echo paths usually carry highly cross-correlated signals, the normal equation to be solved for the minimization of the residual echo is often ill-conditioned or has infinitely many solutions depending on the transmission channels. In other words, straightforward generalization of monaural echo canceler to stereophonic one suffers from lacking sufficient condition to determine the unique pair of echo paths, which is the so-called non-uniqueness problem [1–6]. A great deal of effort has been devoted to achieve the unique pair [3, 6–9]. In particular, it was reported that applying a periodically delayed input to the NLMS helps SAECRs achieve lower miss-identification of echo paths with little audible degradation [6, 7]. This simple method is called *input sliding technique*. Some convergence analyses of the technique have also been reported [10, 11]. From another point of view, the statistical nature of the input signals depends on the acoustic paths in the transmission room, which may vary with ambient temperature etc., or may be dynamically modified by movement of objects; e.g., human bodies or doors [12]. Therefore fast tracking is strongly required. Moreover, because of the 2 audio channels, we have to identify the impulse responses of all 4 acoustic paths, from 2 loudspeakers to 2 microphones, by adapting the 4 echo cancelers. Therefore the adaptive algorithm, employed in the system, must be of low computational complexity. Establishing such an efficient algorithm is the major interest in the study of the SAECRs [13].

The NLMS algorithm has been widely used in acoustic echo canceler due to its simplicity and robustness to noise. However, unfortunately it shows slow convergence, even in the single channel case, for a colored input signal like a speech [14]. To improve convergence speed, the use, in place of NLMS, of more sophisticated algorithm, APA [15, 16], would be conceivable. However, APA causes huge computational cost for high dimensional affine projection, moreover, the performance of more than two dimensional affine projection is severely influenced by noise (see [17]). On the other hand, to resolve these difficulties, an adaptive filtering algorithm based on the *adaptive parallel subgradient projection (PSP) techniques* was recently established [17]. The algorithm is computationally efficient and robust to noise, and in addition, exhibits dramatically fast and stable convergence. In [18], the straightforward application of the algorithm in [17] to Stereophonic Acoustic Echo Cancellation (SAEC) was presented, which exhibits fast and stable convergence even in noisy situation. However [18] does not utilize the preprocessing of the input sliding technique unlike [6, 7, 10, 11].

In this paper, we present an efficient robust filtering scheme, for SAEC, based on the *adaptive parallel subgradient projection (PSP) techniques* combined with the *input sliding technique.* The scheme simultaneously uses information both in the current and previous periods of the input sliding technique while the original method in [6, 7] just uses information in the current period. Robustness to noise is achieved by introducing the stochastic property sets. Moreover it requires only linear computational complexity because it is free from solving systems of linear equations. The simulation result shows that the proposed scheme achieves, even in noisy situation, excellent improvements in Echo Return Loss Enhancement (ERLE) and miss-identification as well as in convergence speed.

2. PRELIMINARIES

2.1. Notations

Let $\mathbb{N}$ and $\mathbb{R}$ denote the sets of all non-negative integers and real numbers respectively. Define also $\mathbb{N}^* := \mathbb{N}\backslash\{0\}$. Let $k \in \mathbb{N}$ denote the time index. We use the length ($M \in \mathbb{N}^*$) of the impulse responses of transmission room and the length ($N \in \mathbb{N}^*$) of the impulse responses of receiving room. For simplicity, we also use the same notation N for the length of the filters. Given $N \in \mathbb{N}^*$, $\mathcal{H} := \mathbb{R}^{2N}$ is a real Hilbert space equipped with the inner product $\langle \boldsymbol{x}, \boldsymbol{y} \rangle := \boldsymbol{x}^t \boldsymbol{y}$, $\forall \boldsymbol{x}, \boldsymbol{y} \in \mathcal{H}$, and its induced norm $\|\boldsymbol{x}\| := \left(\boldsymbol{x}^t \boldsymbol{x}\right)^{1/2}$, $\forall \boldsymbol{x} \in \mathcal{H}$, where the superscript t stands for transposition. For any nonempty closed convex set $C \subset \mathcal{H}$, the *projection operator* $P_C : \mathcal{H} \to C$ is defined by $\|\boldsymbol{x} - P_C(\boldsymbol{x})\| = \min_{\boldsymbol{y} \in C} \|\boldsymbol{x} - \boldsymbol{y}\|, \forall \boldsymbol{x} \in \mathcal{H}$. The notation $|S|$ stands for the cardinality of a set S. Vectors and matrices are represented by bold-faced lower-case and upper-case characters respectively. By the talker's speech signal $\boldsymbol{s}_k := [s_k, s_{k-1}, \ldots, s_{k-M+1}]^t \in \mathbb{R}^M$ ($k \in \mathbb{N}$) and the i-th transmission path $\boldsymbol{\theta}_{(i)} \in \mathbb{R}^M$ $(i = 1, 2)$, the

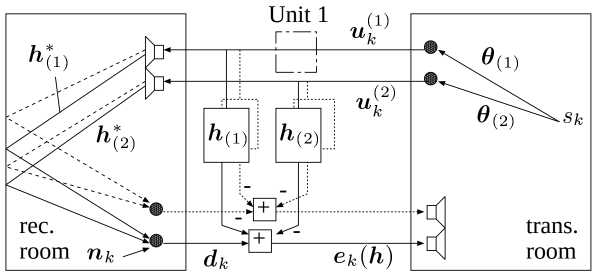


Fig. 1. Stereophonic acoustic echo canceler (SAECR); Unit 1 is a modification unit (see Fig. 2). Without the unit, this figure illustrates a standard system of SAECR.

input to the i-th microphone is generated as $u_k^{(i)} := \boldsymbol{s}_k^t \boldsymbol{\theta}_{(i)}$ $(i = 1, 2)$. Define the i-th input vector sequence $\left(\boldsymbol{u}_k^{(i)}\right)_{k\in\mathbb{N}} \subset \mathbb{R}^N$ as $\boldsymbol{u}_k^{(i)} := \left[u_k^{(i)}, u_{k-1}^{(i)}, \ldots, u_{k-N+1}^{(i)}\right]^t \in \mathbb{R}^N, \quad k \in \mathbb{N}$. For $r \in \mathbb{N}^*$, we use $\boldsymbol{U}_k^{(i)} := \left[\boldsymbol{u}_k^{(i)}, \boldsymbol{u}_{k-1}^{(i)}, \ldots, \boldsymbol{u}_{k-r+1}^{(i)}\right] \in \mathbb{R}^{N\times r}$. Suppose that $\boldsymbol{h}^*_{(i)} \in \mathbb{R}^N$ stands for the i-th receiving echo path to be estimated, and $\boldsymbol{n}_k := [n_k, \ldots, n_{k-r+1}]^t \in \mathbb{R}^r$, $\forall k \in \mathbb{N}$, is the observed noise vector at the microphone in the receiving room. Then the *data process vector* $(\boldsymbol{d}_k)_{k\in\mathbb{N}} \subset \mathbb{R}^r$ is modeled as $\boldsymbol{d}_k := [d_k, \ldots, d_{k-r+1}]^t := \boldsymbol{U}_k^t \boldsymbol{h}^* + \boldsymbol{n}_k, \quad \forall k \in \mathbb{N}$, where $\boldsymbol{h}^* := \left[{\boldsymbol{h}^*_{(1)}}^t, {\boldsymbol{h}^*_{(2)}}^t\right]^t \in \mathcal{H}$ and $\boldsymbol{U}_k := \left[{\boldsymbol{U}_k^{(1)}}^t {\boldsymbol{U}_k^{(2)}}^t\right]^t \in \mathbb{R}^{2N\times r}$. Let $\boldsymbol{h}_{(i)} \in \mathbb{R}^N$ be (the impulse response of) the i-th echo canceler, an *estimate* of $\boldsymbol{h}^*_{(i)}$ for $i = 1, 2$. Then we define, with $\boldsymbol{h} := \left[{\boldsymbol{h}_{(1)}}^t, {\boldsymbol{h}_{(2)}}^t\right]^t \in \mathcal{H}$ and $\boldsymbol{u}_k := \left[{\boldsymbol{u}_k^{(1)}}^t, {\boldsymbol{u}_k^{(2)}}^t\right]^t \in \mathcal{H}$, the *estimation residual* functions $e_k : \mathcal{H} \to \mathbb{R}$ by $e_k(\boldsymbol{h}) := \boldsymbol{u}_k^t \boldsymbol{h} - d_k, \quad \forall k \in \mathbb{N}$.

2.2. Non-Uniqueness Problem in Stereophonic Acoustic Echo Cancellation

We focus, without loss of generality, on the identification of the echo paths from all the loudspeakers to an arbitrary specified microphone in the receiving room. The ultimate goal of SAEC is to identify the possibly changing $\boldsymbol{h}^* \in \mathcal{H}$ even in the noisy situations. For simplicity, however, in the following two subsections, we review the problem only in noise free situations; i. e., $n_k = 0, \forall k \in \mathbb{N}$. In this case, because we can observe only $\left(u_k^{(i)}\right)_{k\in\mathbb{N}}$ and $(d_k)_{k\in\mathbb{N}}$, all what we can do is to find a point in

$$\mathcal{V} := \{\boldsymbol{h} \in \mathcal{H} : \ e_k(\boldsymbol{h}) = 0, \ \forall k \in \mathbb{N}\}. \tag{1}$$

Unfortunately, $\mathcal{V}$ is, in general, not a *singleton*, which is the *non-uniqueness problem*.

2.3. Input Sliding Technique

In this section, we introduce the input sliding technique [6, 7]. Let $Q, T \in \mathbb{N}^*$ $(Q > T)$ denote the one-cycle period for modifications and the transition period for smoothness respectively. Define the periodically delayed signal [1]

$$\widetilde{\boldsymbol{u}}_k^{(1)} = c_k \boldsymbol{u}_k^{(1)} + (1 - c_k)\, \boldsymbol{u}_{k-1}^{(1)}, \tag{2}$$

[1]Without loss of generality, we modify the input signal $\boldsymbol{u}_k^{(1)}$ in the first channel. In (2), we can also use any other modified signal in stead of $\boldsymbol{u}_{k-1}^{(1)}$. Note that, however, careful investigation should be required in order not to cause a serious audible degradation to the speech signal.

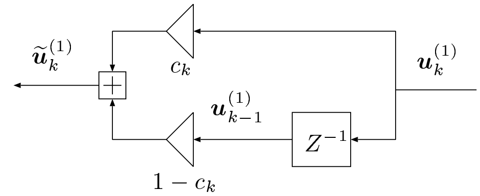


Fig. 2. The modification unit. The Unit 1 in Fig. 1 is replaced by this unit.

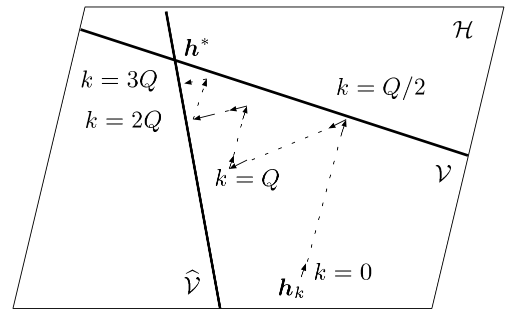


Fig. 3. A geometric interpretation of the original input sliding technique in the noiseless situation.

where $(c_k)_{k\in\mathbb{N}}$ is the periodic sequence defined as, for $0 \le k \le Q$,

$$c_k := \begin{cases} 1, & 0 \le k \le \frac{Q-T}{2}, \\ 1 \longrightarrow 0, & \frac{Q-T}{2} < k \le \frac{Q}{2}, \\ 0, & \frac{Q}{2} < k \le Q - \frac{T}{2}, \\ 0 \longrightarrow 1, & Q - \frac{T}{2} < k \le Q, \end{cases} \tag{3}$$

where $\longrightarrow$ means the smooth transition. $(c_k)_{0\le k\le Q}$ is extended periodically for $k \in \mathbb{N}$. Thus $\widetilde{\boldsymbol{u}}_k^{(1)}$ alternatively changes between the original signal $\boldsymbol{u}_k^{(1)}$ and the delayed signal $\boldsymbol{u}_{k-1}^{(1)}$. The modification unit is depicted in Fig. 2.

Define the solution space, constructed by the delayed input signals, $\widehat{\mathcal{V}} := \left\{\boldsymbol{h} \in \mathcal{H} : \ \widehat{\boldsymbol{u}}_k^t \boldsymbol{h} - \widehat{d}_k = 0, \ \forall k \in \mathbb{N}\right\}$, where $\widehat{\boldsymbol{u}}_k := \left[\left(\boldsymbol{u}_{k-1}^{(1)}\right)^t, \left(\boldsymbol{u}_k^{(2)}\right)^t\right]^t$ and $\widehat{d}_k := \widehat{\boldsymbol{u}}_k^t \boldsymbol{h}^*$ (see Sec. 2.2). Since the simple use of the input sliding technique accounts the only current information, the echo cancelers approach to the target $\boldsymbol{h}^*$ through an indirect way as shown in Fig. 3. The simultaneous use of information both in the previous and current periods could lead to faster convergence to the target $\boldsymbol{h}^*$. In the following section, we present an efficient robust adaptive scheme based on the adaptive parallel subgradient projection techniques [17] with the input sliding technique.

3. EFFICIENT ROBUST ADAPTIVE FILTERING SCHEME FOR INPUT SLIDING TECHNIQUE

Let $\left(\widetilde{\boldsymbol{U}}_k\right)_{k\in\mathbb{N}} \subset \mathbb{R}^{2N\times r}$ and $\left(\widetilde{\boldsymbol{d}}_k\right)_{k\in\mathbb{N}} \subset \mathbb{R}^r$ denote the modified signal sequences corresponding to $(\boldsymbol{U}_k)_{k\in\mathbb{N}}$ and $(\boldsymbol{d}_k)_{k\in\mathbb{N}}$ respectively. We define the stochastic property set

$$C_k(\rho) := \left\{\boldsymbol{h} \in \mathcal{H} : g_k(\boldsymbol{h}) := \|\widetilde{e}_k(\boldsymbol{h})\|^2 - \rho \le 0\right\}, \tag{4}$$

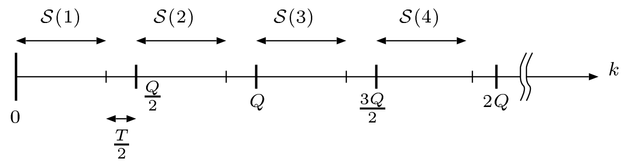


Fig. 4. The time interval of modification.

where $\widetilde{e}_k(\boldsymbol{h}) := \widetilde{\boldsymbol{U}}_k^t \boldsymbol{h} - \widetilde{\boldsymbol{d}}_k$ and $\rho \geq 0$. For given $Q, T \in \mathbb{N}^*$, let $\mathcal{S}(p) := \left\{ k \in \mathbb{N} : \frac{(p-1)Q}{2} \leq k \leq \frac{pQ-T}{2} \right\}$, $p \in \mathbb{N}^*$, denote the set of all the time indexes in the p-th interval of modification as shown in Fig. 4 ($\mathcal{S}(0) := \emptyset$).

For given $q \in \mathbb{N}^*$, define the index sets $I_k := \{k, k-1, \ldots, k-q+1\} \subset \mathbb{N}$ and $J_k \subset \mathcal{S}(p(k))$, where $p(k) := \lfloor (2k+T)/Q \rfloor$, $\forall k \in \mathbb{N}$. Also define the weight $w_\iota^{(k)} > 0$, $\forall \iota \in I_k \cup J_k, \forall k \in \mathbb{N}$, to satisfy $\sum_{\iota \in I_k} w_\iota^{(k)} + \sum_{\iota \in J_k} w_\iota^{(k)} = 1, \forall k \in \mathbb{N}$. The proposed adaptive filtering scheme is given as follows.

Scheme 1 *For an arbitrary given $\boldsymbol{h}_0 \in \mathcal{H}$, define $(\boldsymbol{h}_k)_{k \in \mathbb{N}} \subset \mathcal{H}$ by*

$$\boldsymbol{h}_{k+1} = \boldsymbol{h}_k + \mu_k \left(\sum_{\iota \in I_k} w_\iota^{(k)} P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) + \sum_{\iota \in J_k} w_\iota^{(k)} P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right), \quad \forall k \in \mathbb{N}, \tag{5}$$

where

$$P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}) = \begin{cases} \boldsymbol{h} + \frac{-g_\iota(\boldsymbol{h}_k) + (\boldsymbol{h}_k - \boldsymbol{h})^t \nabla g_\iota(\boldsymbol{h}_k)}{4 \tilde{\boldsymbol{e}}_\iota^t(\boldsymbol{h}_k) \left\{ \tilde{\boldsymbol{U}}_\iota^t \tilde{\boldsymbol{U}}_\iota + \delta \boldsymbol{I} \right\} \tilde{\boldsymbol{e}}_\iota(\boldsymbol{h}_k)} \nabla g_\iota(\boldsymbol{h}_k), \\ \quad \text{if } \boldsymbol{h} \notin H_\iota^-(\boldsymbol{h}_k), \\ \boldsymbol{h}, \quad \text{otherwise}, \end{cases} \tag{6}$$

$H_\iota^-(\boldsymbol{y}) := \{ \boldsymbol{x} \in \mathcal{H} : (\boldsymbol{x} - \boldsymbol{y})^t \nabla g_\iota(\boldsymbol{y}) + g_\iota(\boldsymbol{y}) \leq 0 \}$, $\delta \geq 0$ *is the regularization parameter and* $\mu_k \in [0, 2\mathcal{M}_k]$ *is the step size, where* $\mathcal{M}_k$ *is defined as*

$$\begin{cases} \frac{\sum_{\iota \in I_k} w_\iota^{(k)} \left\| P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right\|^2 + \sum_{\iota \in J_k} w_\iota^{(k)} \left\| P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right\|^2}{\left\| \sum_{\iota \in I_k} w_\iota^{(k)} P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) + \sum_{\iota \in J_k} w_\iota^{(k)} P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right\|^2}, \\ \quad \text{if } \boldsymbol{h}_k \notin \bigcap_{\iota \in \{I_k \cup J_k\}} H_\iota^-(\boldsymbol{h}_k), \\ 1, \quad \text{otherwise}. \end{cases}$$

(NOTE: If $\delta = 0$, $P^{(\delta)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h})$ is reduced to the exact projection from $\boldsymbol{h}$ onto the closed half-space $H_\iota^-(\boldsymbol{h}_k)$; i. e., $P^{(0)}_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}) = P_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h})$). Clearly, by (5) and (6), the algorithm is free from the computational load of solving a system of linear equations to update the estimate $\boldsymbol{h}_{k+1}$ from $\boldsymbol{h}_k$, unlike the APA scheme for $r \geq 2$. Moreover a simple inspection of the summation in (5) implies that the algorithm is well suited for $q + |J_k|$ concurrent processors. (NOTE: It is not hard to see that the method in [6, 7] is the simplest case, where $w_k^{(k)} = 1$, $w_\iota^{(k)} = 0$ ($\forall \iota \neq k$), $r = 1$, $\rho = 0$). A geometric interpretation of Scheme 1 is given in Fig. 5.

In Scheme 1, the monotonicity $\|\boldsymbol{h}_{k+1} - \boldsymbol{h}^*\| \leq \|\boldsymbol{h}_k - \boldsymbol{h}^*\|$ is guaranteed if $\boldsymbol{h}^* \in \bigcap_{\iota \in I_k \cup J_k} H_\iota^-(\boldsymbol{h}_k)$ [17, Proposition 1]. Under the practical assumption of the noise process of zero mean i.i.d. Gaussian random variables $\mathcal{N}(0, \sigma^2)$, a systematic design of the stochastic property set $C_k(\rho)$ was proposed based on the following simple formulae for ρ that rely only on r and on the variance σ^2 of the corrupting noise process $(n_k)_{k \in \mathbb{Z}}$.

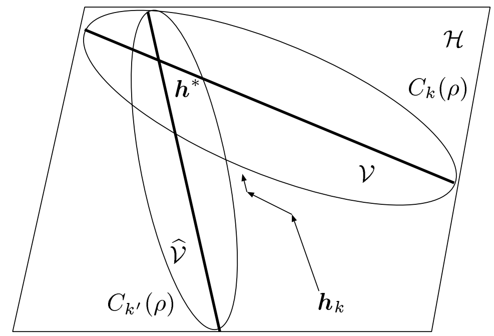


Fig. 5. A geometric interpretation of Scheme 1. k: current time index, k': a time index in the previous period $\mathcal{S}(p(k))$. For each time k, $\boldsymbol{h}_k$ monotonically approaches to the intersection of $C_k(\rho)$ and $C_{k'}(\rho)$.

Example 1 [17] *(Design of Stochastic Property Sets)* $\rho_1 := (r + \sqrt{2r})\sigma^2 \geq \rho_2 := r\sigma^2 \geq \rho_3 := \max\{(r-2)\sigma^2, 0\}$.

4. NUMERICAL EXAMPLE

To compare the performance of Scheme 1 to the NLMS [6, 7], based on the structure of input sliding technique, for estimating $\boldsymbol{h}^* \in \mathcal{H} := \mathbb{R}^{512}$ ($N = M = 256$), a simulation test was performed under the noise situation of SNR:$= 10\log_{10}\left(E\left\{z_k^2\right\}/E\left\{n_k^2\right\}\right) = 25$ dB, where $z_k := \boldsymbol{u}_k^t \boldsymbol{h}^*$ and E denotes *expectation*. In the modification unit, we set $Q = 800$ and $T = 80$. We utilized a male's speech signal, which was sampled at 16kHz, as the input $(s_k)_{k \in \mathbb{N}}$. For the NLMS algorithm, the step size was set to 0.2 by following a recommendation given in [6, 7]. For a fair comparison (see [19]), the proposed scheme employed $\mu_k = 0.4\mathcal{M}_k$, $\forall k \in \mathbb{Z}$, $\rho = \rho_3$ (see Example 1) and $r = 1$. For the present numerical test, we focus on the special cases: (a) $q = 5$ and $J_k := \{k - Q/2 - j\}_{j=0}^4$, $\forall k \in \mathbb{N}$, and (b) $q = 10$ and $J_k = \emptyset$, $\forall k \in \mathbb{N}$. We let $w_\iota^{(k)} := 1/10$, $\forall k \in \mathbb{N}, \forall \iota \in I_k \cup J_k, \forall k \in \mathbb{N}$. (NOTE: Proposed (b) corresponds to the straightforward application of adaptive PSP algorithm [17] to input sliding technique, on the other hand, proposed (a) uses the information both in the current and previous periods simultaneously). For a faster and more stable convergence, the regularization parameter δ was set to 1.0×10^{-2} both for the NLMS and for Scheme 1.

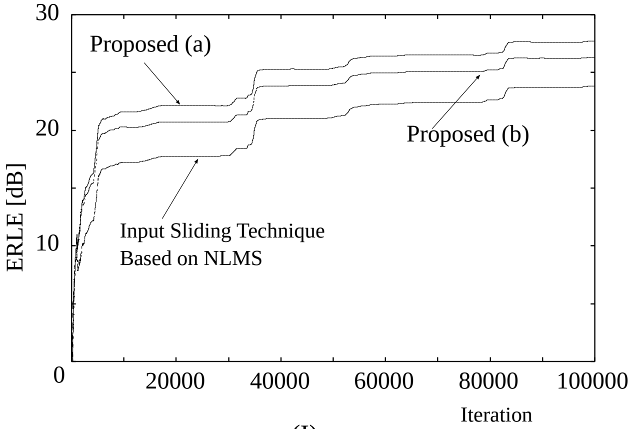
We evaluate the system mismatch defined as $\|\boldsymbol{h}^* - \boldsymbol{h}_k\|^2 / \|\boldsymbol{h}^*\|^2$, $\forall k \in \mathbb{N}$, as well as

$$\text{ERLE}(k) := 10\log_{10} \frac{\sum_{i=1}^k (z_i)^2}{\sum_{i=1}^k (z_i - \boldsymbol{u}_i^t \boldsymbol{h}_i)^2}.$$

Fig. 6 shows that the proposed scheme outperforms the NLMS based method. Furthermore, we observe that it is effective to use the data both in the previous and current periods simultaneously for faster convergence.

5. CONCLUSION

In this paper, we present an efficient robust adaptive filtering scheme for the SAEC problem. The proposed scheme is based on the adaptive parallel subgradient projection techniques combined with the input sliding technique. The scheme could approach to the target echo paths directly because of the simultaneous use of information both in the current and previous periods of the input sliding technique, while the original technique just uses information in the



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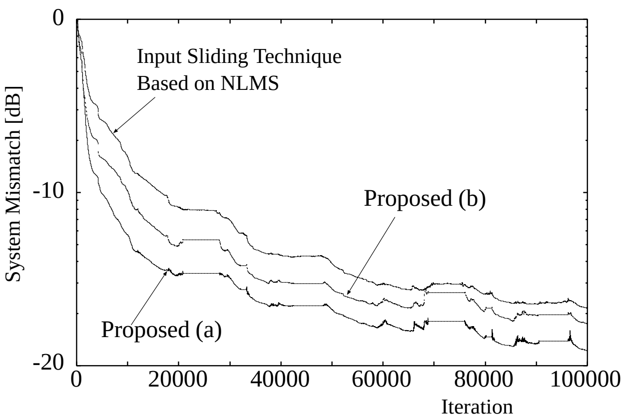

(II)

Fig. 6. Proposed scheme versus NLMS based on the structure of input sliding technique under SNR: 25dB. For a fair comparison, step size is set to 0.2 (NLMS) and $0.4\mathcal{M}_k$ (Proposed). We let $r = 1$, $\rho = \rho_3$, (a) $q = 5$ and $J_k := \{k - Q/2 - j\}_{j=0}^{4}$, (b) $q = 10$ and $J_k = \emptyset$.

current period. The numerical example shows that it can achieve, even in noisy situation, much faster convergence as well as lower miss-identification of echo paths and higher ERLE than the conventional technique.

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